Quality and Performance Optimization through Generative Adversarial Networks based Anomaly Detection

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Quality & Performance Optimization through GAN-based Anomaly Detection : Industrial & Medical Use Cases

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Context

- Industrial sector evolved with technologies : current era of cyber-physical systems / Industry 4.0.
- Advanced anomaly detection : crucial quality control step / important part of Industry 4.0 opportunities.
- Traditional algorithms suffers from practical drawbacks like high false positive rates and human misjudgment.

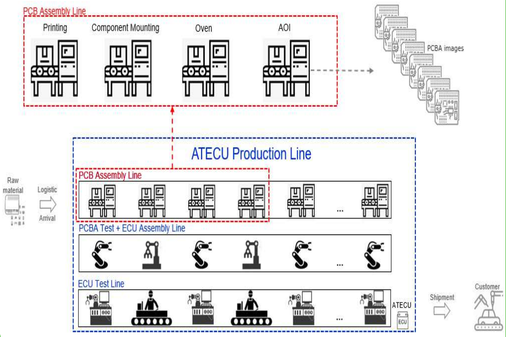


Figure 1: PCBA Manufacturing Process Flow

Research Questions

- What are the best deep learning techniques to detect anomalies that exist in real-world industrial datasets? (unsupervised learning, high-resolution images, imbalanced datasets, etc.)
- How to integrate the business constraints (full TPR, acceptable inference time, worker interactions, explainable decisions, etc.) into a binary normal/abnormal classification algorithm?

Methods & Materials

First Idea GanoDIP [1]:

- Train a Generator and a Discriminator through a GAN framework. Place the networks in an autoencoder architecture in order to train an Encoder.
- At the inference step, an anomaly score qualifies the differences on the residual image, after a patching technique that highlights the differences.

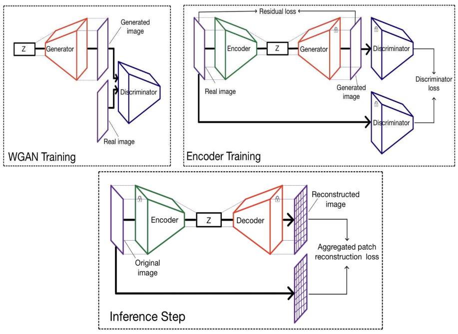


Figure 2: GanoDIP Training and Inference Networks Architecture

Second Idea VQGanoDIP [2]:

- Represent the images as a composition of coherent and rich details in the latent space, through a Vector Quantized GAN.
- Statistics on the residual image and the networks losses quantify how the image is different from the normality.
- A binary extra tree classifier is finally used to discriminate between normal and abnormal products.

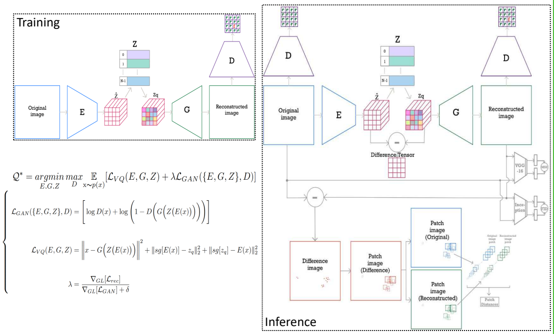


Figure 3: VQGanoDIP Training and Inference Networks Architecture

Another approach developed [3]:

- Take the few abnormal data available into consideration, in order to train a cycle-GAN.
- Industrial and medical datasets have been considered.

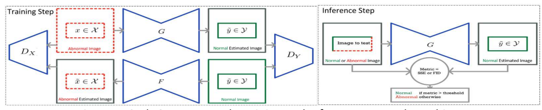
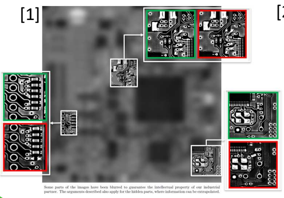
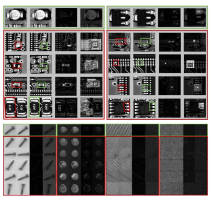


Figure 4: CycleGAN Approach Training and Inference Networks Architecture

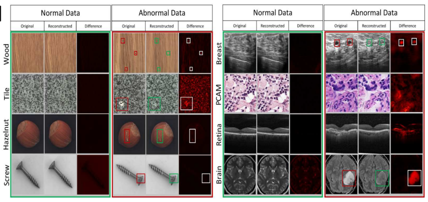
[1]



[2]



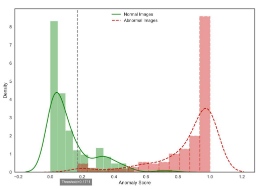
[3]



Results

[2] VQGAN-based approach on the PCBA dataset :

- Regular accuracy = 95.69%.
- Zero-False-Negative accuracy = 87.93%.



Dataset (Classifier)	Accuracy(%)↑ STD	ZFN
PCBA (ET)	95.69	87.93
Cable (XGBoost)	76.82	57.94
Carpet (LR)	85.6	50.21
Grid (LR)	95.98	85.43
Hazelnut (LGBM)	98.95	98.25
Leather (XGBoost)	92.17	90.43
Screw (ADA)	93	83.67
Transistor (LGBM)	88.7	49.15
Zipper (LGBM)	92.55	81.57

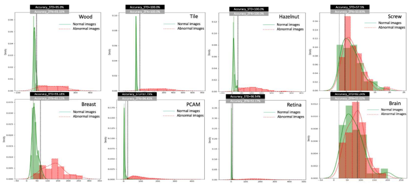
Quality: 37%
False Positives saved

Performance: 72%
Inspection time saved

Figure 5: Qualitative and Quantitative Results for the VQGanoDIP Approach

[3] CycleGAN-based approach on the texture-shaped industrial & medical datasets :

- Regular accuracy = 97.2%.
- Zero-False-Negative accuracy = 85.4%.



			Anomaly Score = FID		*Anomaly Score = SSE*	
Dataset	*Domain*	*Type*	*ZFN thr.*	*ACC thr.*	*ZFN thr.*	*ACC thr.*
Wood	Indust.	Texture	93.33	**95.00**	73.33	83.33
Tile	Indust.	Texture	**100.00**	**100.00**	89.02	97.56
Hazelnut	Indust.	Object	**100.00**	**100.00**	72.86	94.29
Screw	Indust.	Object	50.83	**57.50**	52.50	52.50
Breast	Med.	Texture	65.15	93.18	87.12	**94.70**
PCAM	Med.	Texture	94.41	97.79	82.42	**99.89**
Retina	Med.	Texture	52.17	**96.54**	50.29	95.46
Brain	Med.	Object	51.02	62.24	62.24	**68.37**

Figure 6: Qualitative and Quantitative Results for the CycleGAN Approach

Future Works & References

- Different Generative Networks will be considered to improve the residual image generation to focus on the real anomalies.
- The quality constraint will be applied directly at the training step as a future work. The Augmented Lagrangian Method is under study to improve the current performance.
- The method integration into the real-world production line will also be explored, considering the company philosophy, constraints, and the workers' habits.

[1] Bougaham, A. et al. (2021). GanoDIP - GAN Anomaly Detection through Intermediate Patches: a PCBA Manufacturing Case. PMLR.
[2] Bougaham, A. et al. (2022). Composite Score for Anomaly Detection in Imbalanced Real-World Industrial Dataset. arXiv preprint.
[3] Bougaham, A. et al. (2023). Industrial and Medical Anomaly Detection Through Cycle-Consistent Adversarial Networks. arXiv preprint.

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